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Introduction

Steepest descent
(SD)Non-Linear
Conjugate
gradient (CG)

Results

Conclusions

Conjugate Directions in Landau and Coulomb Lattice Gauge Fixing

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Overview

- Matching lattice Green's functions to continuum perturbation theory, non perturbative renormalisation in Landau gauge.
- Coulomb gauge fixed wall source propagators, static potential measurements.
- Two schools
 - 1 Los Alamos
 - 2 Cornell
 - Overrelaxation
 - Fourier acceleration

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Links, Fields and Notation

$$U_\mu \left(x + a \frac{\hat{\mu}}{2} \right) = e^{i a g_0 A_\mu \left(x + a \frac{\hat{\mu}}{2} \right)}.$$

Generally for an SU(3) matrix $U = e^{iA} = f_0 + f_1 A + f_2 A^2$.

$$A \approx \frac{1}{2i} \left\{ [U - U^\dagger] - \frac{1}{3} \text{Tr} [U - U^\dagger] \cdot I_{3 \times 3} \right\}.$$

$$A = \frac{f_2^* U - f_2 U^\dagger - 2i \Im(f_0 f_2^*) \cdot I_{3 \times 3}}{2i \Im(f_1 f_2^*)}.$$

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Links, Fields and Notation ... Cont'd

$$a\Delta_\mu A_\mu(x) = \sum_\mu \left(A_\mu \left(x + a\frac{\hat{\mu}}{2} \right) - A_\mu \left(x - a\frac{\hat{\mu}}{2} \right) \right).$$

$$\Theta^{(n)} = \frac{1}{N_c V} \sum_x \text{Tr} \left[\left(a\Delta_\mu a g_0 A_\mu^{(n)}(x) \right)^2 \right].$$

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Fixing on a lattice ... Steepest descent (SD)

Satisfying the Landau condition is the same as minimising a cost functional $F(U)$.

$$F(U) = \frac{1}{N_d N_c V} \sum_{x,\mu} \text{Tr} \left[\left(a g_0 A_\mu \left(x + a \frac{\hat{\mu}}{2} \right) \right)^2 \right].$$

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Fixing on a lattice ... Steepest descent (SD)

Satisfying the Landau condition is the same as minimising a cost functional $F(U)$.

$$F(U) \approx 1 - \frac{1}{N_d N_c V} \sum_{x,\mu} \Re \left(\text{Tr} \left[U_\mu \left(x + a \frac{\hat{\mu}}{2} \right) \right] \right).$$

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$$x^{(n+1)} = x^{(n)} - \alpha f'(x^{(n)}).$$

$0 < \alpha < 1$ is a small tuning parameter.

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$$g(x) = e^{-i\alpha a \Delta_\mu a g_0 A_\mu^{(n)}(x)},$$

$$U_\mu^{(n+1)} \left(x + a \frac{\hat{\mu}}{2} \right) = g(x) U_\mu^{(n)} \left(x + a \frac{\hat{\mu}}{2} \right) g(x + a \hat{\mu})^\dagger.$$

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Fourier Acceleration (FA)

Davies et al. (1988) pointed out that the SD suffers from critical slowing down. Ameliorated by Fourier acceleration

$$g(x) = e^{-i\alpha a \Delta_\mu a g_0 A_\mu^{(n)}(x)}.$$

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Fourier Acceleration (FA)

Davies et al. (1988) pointed out that the SD suffers from critical slowing down. Ameliorated by Fourier acceleration

$$g(x) = e^{-i\alpha \tilde{F} \frac{p_{\text{Max}}^2}{Vp^2} F a \Delta_\mu a g_0 A_\mu^{(n)}(x)}.$$

$$p^2 = 2 \left(N_d - \sum_\mu \cos \left(\frac{2\pi n_\mu}{L_\mu} \right) \right).$$

We call this the FASD method.

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Optimal SD is far from optimal

- What about $\alpha = \alpha_n$, tuned at each step?
- Evaluate “N” probe α'_n ’s and choose the one that minimises $F(U)$ best
- Use cubic spline interpolation and exact solve for minimum
- Cost is $\approx N \times$ that of fixed α .

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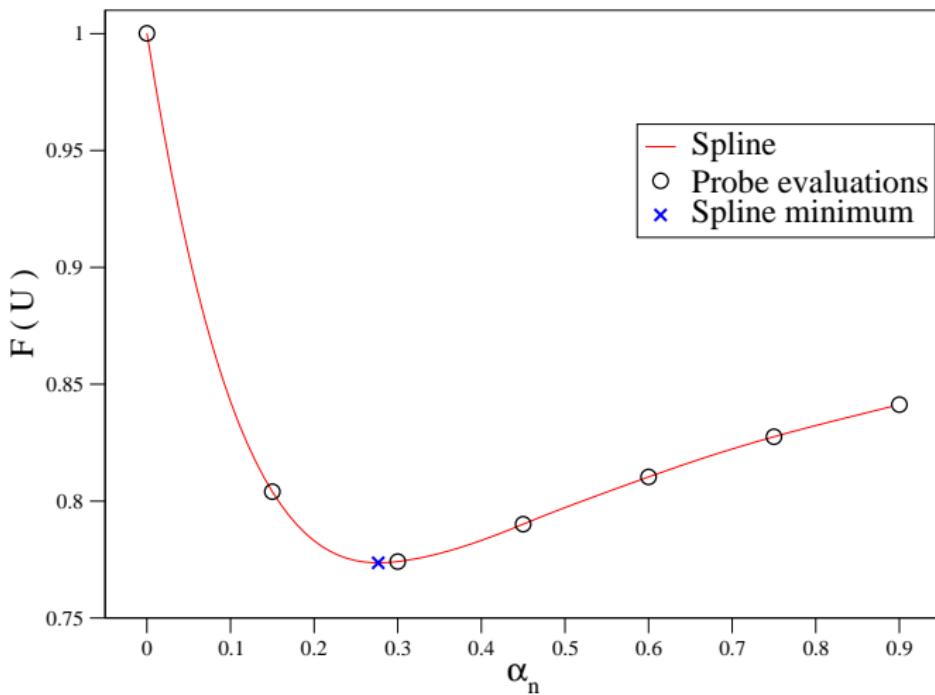
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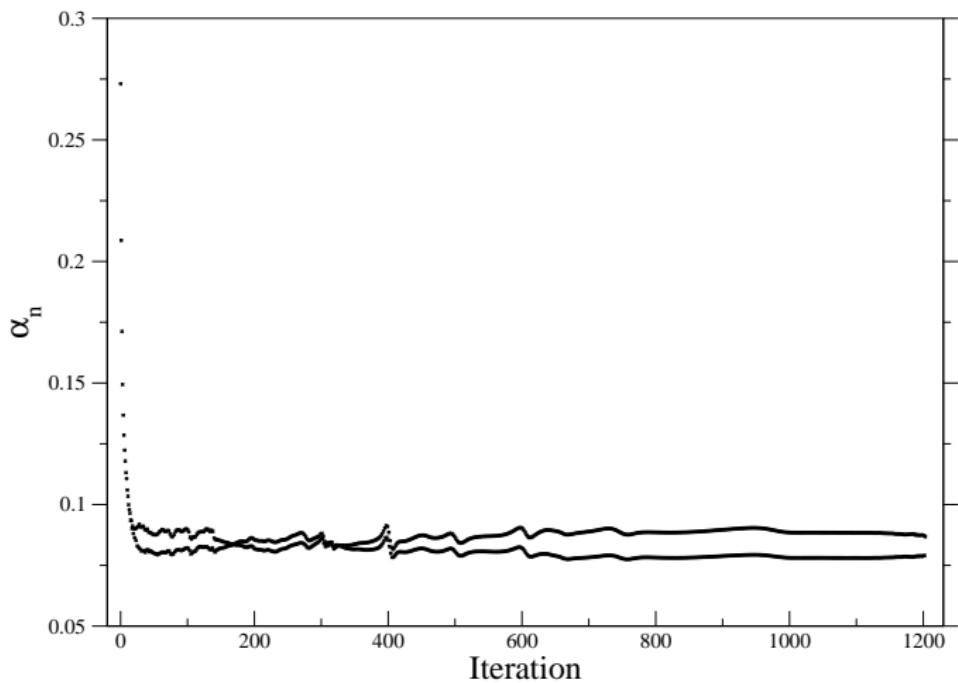
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The general Non-linear CG procedure

Compute the gradient direction $f'(x_0)$

Perform a line search for α_0 s.t $\min(f(x_0 - \alpha_0 f'(x_0)))$

Perform the update $x_1 = x_0 - \alpha_0 f'(x_0)$

Set $s_0 = -f'(x_0)$

$n = 1$

while $|f'(x_n)|^2 > \text{Tolerance}$ **do**

 Compute the gradient $f'(x_n)$

 Compute $\beta_n = \max \left[0, \frac{f'(x_n)^T (f'(x_n) - f'(x_{n-1}))}{f'(x_{n-1})^T f'(x_{n-1})} \right]$

 Conjugate direction $s_n = -f'(x_n) + \beta_n s_{n-1}$

 Perform a line search for α_n s.t $\min(f(x_n + \alpha_n s_n))$

 Update $x_{n+1} = x_n + \alpha_n s_n$

$n = n + 1$

end while

The general Non-linear CG procedure

$$\Gamma_0(x) \leftarrow a\Delta_\mu a g_0 A_\mu^{(0)}(x)$$

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$$\Gamma_0(x) \leftarrow \tilde{F} \frac{p_{\text{Max}}^2}{Vp^2} Fa \Delta_\mu a g_0 A_\mu^{(0)}(x)$$

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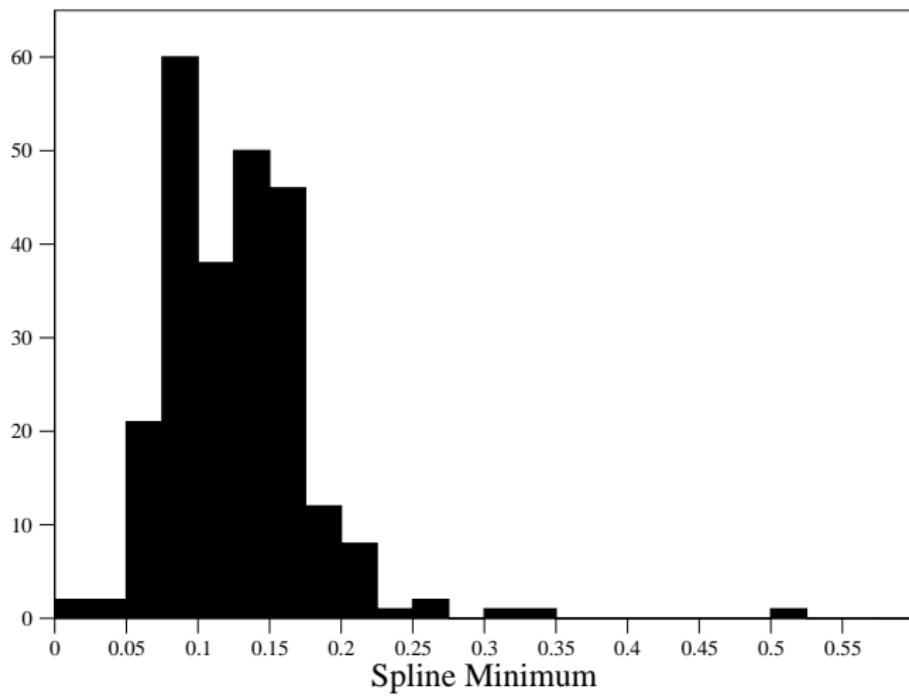
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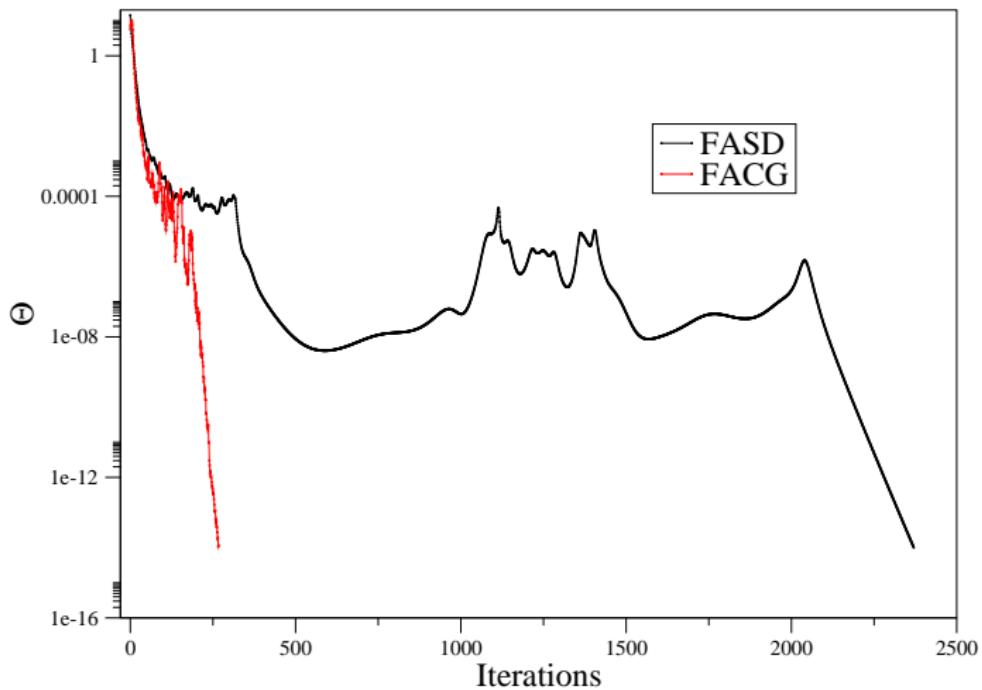
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FASD vs. FACG



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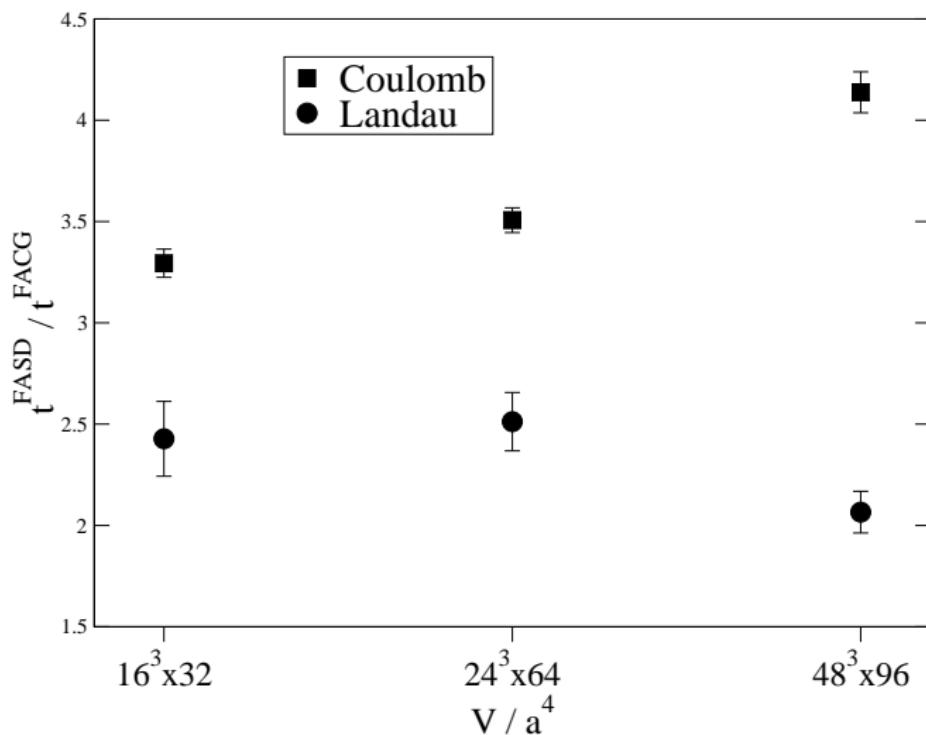
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Effective speed up



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Timings

Volume	Landau		Coulomb	
	FASD (s)	FACG (s)	FASD (s)	FACG (s)
$16^3 \times 32$	25(1)	10.5(5)	27.4(6)	8.3(1)
$24^3 \times 64$	306(18)	122(7)	194(3)	55.4(4)
$48^3 \times 96$	12995(857)	6292(404)	10882(180)	2629(39)

Table: The time in seconds taken to achieve an accuracy of $\Theta^{(n)} < 10^{-14}$ for 25 randomly transformed copies of the same, well-thermalised configuration. Each configuration has the same lattice spacing. This measurement was performed using four 8-core AMD Opteron 6128 processors. All operations were performed in double precision.

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Conclusions

- This method relies on fast functional evaluations and a line search
- At least a $2\times$ speed up from this procedure for all volumes considered
- Fewer FFTs compared to the FASD
- Method could be faster
- Check out www.github.com/RJHudspith/GLU/
- And my paper <http://arxiv.org/abs/1405.5812>